REMARKS

Claims 1-21 are pending. Claims 1, 3-7, 9-14, 16-17, and 19-21 stand rejected under 35 U.S.C. § 102(e) as being anticipated by U.S. Patent No. 6,523,026 to Gillis. Claims 2, 8, 15, and 18 stand rejected under 35 U.S.C. § 103(a) as being unpatentable over U.S. Patent No. 6,523,026 to Gillis in view of U.S. Patent No. 5,799,276 to Komissarchik et al.

Reconsideration is requested. No new matter is added. The specification is amended. Claims 1, 6-7, 12-13, and 18-21 are amended. Claims 2, 8, and 15 are canceled. The rejections are traversed. Claims 1, 3-7, 9-14, and 16-21 remain in the case for consideration.

REJECTION OF CLAIMS UNDER 35 U.S.C. §§ 102(e) and 103(a)

Referring to claim 1, the invention is directed toward a computer-implemented method for constructing a single vector representing a semantic abstract in a topological vector space for a semantic content of a document on a computer system, the method comprising: storing a semantic content for the document in computer memory accessible by the computer system; identifying a directed set of concepts as a dictionary, the directed set including a maximal element at least one concept, and at least one chain from the maximal element to every concept; selecting a subset of the chains to form a basis for the dictionary; identifying lexemes/lexeme phrases in the semantic content; measuring how concretely each lexemes/lexeme phrase is represented in each chain in the basis and the dictionary; constructing state vectors in the topological vector space for the semantic content using the measures of how concretely each lexemes/lexeme phrase is represented in each chain in the dictionary and the basis; superpositioning the state vectors to construct the single vector; and storing the single vector as the semantic abstract for the document.

Referring to claim 7, the invention is directed toward a computer-readable medium containing a program to construct a single vector representing a semantic abstract in a topological vector space for a semantic content of a document on a computer system, the program comprising: storing software to store a semantic content for the document in computer memory accessible by the computer system; identification software to identify a directed set of concepts as a dictionary, the

directed set including a maximal element at least one concept, and at least one chain from the maximal element to every concept; selection software to select a subset of the chains to form a basis for the dictionary; identification software to identify lexemes/lexeme phrases in the semantic content; measurement software to measure how concretely each lexemes/lexeme phrase is represented in each chain in the basis and the dictionary; construction software to construct state vectors in the topological vector space for the semantic content using the measures of how concretely each lexemes/lexeme phrase is represented in each chain in the dictionary and the basis; superpositioning software to superposition the state vectors to construct the single vector; and storing software to store the single vector as the semantic abstract for the document.

Referring to claim 13, the invention is directed toward an apparatus on a computer system to construct a single vector representing a semantic abstract in a topological vector space for a semantic content of a document on a computer system, the apparatus comprising: a semantic content stored in a memory of the computer system; a lexeme identifier adapted to identify lexemes/lexeme phrases in the semantic content; a state vector constructor for constructing state vectors in the topological vector space for each lexeme/lexeme phrase identified by the lexeme identifier, the state vectors measuring how concretely each lexeme/lexeme phrase identified by the lexeme identifier is represented in each chain in a basis and a dictionary, the dictionary including a directed set of concepts including a maximal element and at least one chain from the maximal element to every concept in the directed set, the basis including a subset of chains in the directed set; and a superpositioning unit adapted to superposition the state vectors into a single vector as the semantic abstract.

Referring to claim 19, the invention is directed toward a computer-implemented method for constructing minimal vectors representing a semantic abstract in a topological vector space for a semantic content of a document on a computer system, the method comprising: storing a semantic content for the document in computer memory accessible by the computer system; identifying a directed set of concepts as a dictionary, the directed set including a maximal element at least one concept, and at least one chain from the maximal element to every concept; selecting

a subset of the chains to form a basis for the dictionary; identifying lexemes/lexeme phrases in the semantic content; measuring how concretely each lexemes/lexeme phrase is represented in each chain in the basis and the dictionary; constructing state vectors in the topological vector space for the semantic content using the measures of how concretely each lexemes/lexeme phrase is represented in each chain in the dictionary and the basis; locating clumps of state vectors in the topological vector space; superpositioning the state vectors within each clump to form a single vector representing the clump; collecting the single vectors representing each clump to form the minimal vectors; and storing the minimal vectors as the semantic abstract for the document.

Referring to claim 20, the invention is directed toward a computer-readable medium containing a program to construct minimal vectors representing a semantic abstract in a topological vector space for a semantic content of a document on a computer system, the program comprising: storing software to store a semantic content for the document in computer memory accessible by the computer system; identification software to identify a directed set of concepts as a dictionary, the directed set including a maximal element at least one concept, and at least one chain from the maximal element to every concept; section software to select a subset of the chains to form a basis for the dictionary; identification software to identify lexemes/lexeme phrases in the semantic content; measurement software to measure how concretely each lexemes/lexeme phrase is represented in each chain in the basis and the dictionary; construction software to construct state vectors in the topological vector space for the semantic content using the measures of how concretely each lexemes/lexeme phrase is represented in each chain in the dictionary and the basis; clump location software to locate clumps of state vectors in the topological vector space; superpositioning software to superposition the state vectors within each clump to form a single vector representing the clump; collection software to collect the single vectors representing each clump to form the minimal vectors; and storing software to store the minimal vectors as the semantic abstract for the document.

Referring to claim 21, the invention is directed toward an apparatus on a computer system to construct minimal vectors representing a semantic abstract in a topological vector space for a semantic content of a document on a computer system,

the apparatus comprising: a semantic content stored in a memory of the computer system; a state vector constructor for constructing state vectors in the topological vector space for each lexeme/lexeme phrase in the semantic content the state vectors measuring how concretely each lexeme/lexeme phrase is represented in each chain in a basis and a dictionary, the dictionary including a directed set of concepts including a maximal element and at least one chain from the maximal element to every concept in the directed set, the basis including a subset of chains in the directed set; a clump locator unit adapted to locate clumps of state vectors in the topological vector space; a superpositioning unit adapted to superposition the state vectors within each clump into a single vector representing the clump; and a collection unit adapted to collect the single vectors representing the clump into the minimal vectors of the semantic abstract.

In contrast, Gillis teaches a system and method for retrieving semantically distant analogies. Gillis begins by initializing vectors for each term. The vectors are initialized with random values for each component. That way, dot products of pairs of vectors are likely to be close to zero, approximating no relationship between the terms. Then the system works through documents, learning about the terms. The system applies learning laws that correlate nearby words in documents, changing vectors to account for word proximity. The process is repeated until the vectors are stable, at which point they represent the semantics of the words. The system can then construct summary vectors by adding up and normalizing the sum of all vectors for which terms in the document can be found. The summary vector can then be used to locate semantically distant analogies.

It is clear from the above description that Gillis constructs its vectors in a very specific manner, by iteratively scanning a document and applying learning laws. The vectors are initialized with random values, and are modified using the learning laws. In contrast, the vectors in the claimed invention are constructed using basis chains in a directed set, and measuring how concretely a given term is represented in the basis chains. Support for these features can be found in U.S. Patent Application Serial No. 09/512,963, titled "CONSTRUCTION, MANIPULATION, AND COMPARISON OF A MULTI-DIMENSIONAL SEMANTIC SPACE", filed February 25, 2004. This patent application is a continuation-in-part of, and incorporates by reference, U.S.

Patent Application Serial No. 09/615,726, titled "METHOD AND MECHANISM FOR THE CREATION, MAINTENANCE, AND COMPARISON OF SEMANTIC ABSTRACTS", filed July 13, 2000, which is a continuation-in-part of, and incorporates by reference, U.S. Patent Application Serial No. 09/512,963, titled "CONSTRUCTION, MANIPULATION, AND COMPARISON OF A MULTI-DIMENSIONAL SEMANTIC SPACE", filed February 25, 2004. (U.S. Patent Application Serial No. 09/615,726 was amended in a Response to Office Action filed April 16, 2004 to include the above-mentioned claim of priority; the priority claim was not in the application as originally filed.) The Examiner is referred to ancestor U.S. Patent Application Serial No. 09/512,963 for more information, specifically with respect to pages 11-18, wherein the concepts of chains, bases, and how concepts can be measured relative to basis chains are all discussed; copies of these pages and FIGs. 4-5G are attached for the Examiner's reference.

Because neither Gillis nor Komissarchik teach or suggest vector construction according to the features claimed, claims 1, 3-7, 9-14, and 16-21 are patentable under 35 U.S.C. § 102(e) over Gillis and under 35 U.S.C. § 103(a) over Gillis in view of Komissarchik. Accordingly, claims 1, 3-7, 9-14, and 16-21 are allowable.

For the foregoing reasons, reconsideration and allowance of claims 1, 3-7, 9-14, and 16-21 of the application as amended is solicited. The Examiner is encouraged to telephone the undersigned at (503) 222-3613 if it appears that an interview would be helpful in advancing the case.

Respectfully submitted,
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An Example Topology

Consider an actual topology on the set P of predicates. This is accomplished by exploiting the notion of hyponymy and meaning postulates.

Let P be the set of predicates, and let B be the set of all elements of 2^{2^P}, i.e., $\wp(\wp(P))$, that express hyponymy. B is a basis, if not of 2^P, i.e., $\wp(P)$, then at least of everything worth talking about: $S = \cup (b: b \in B)$. If $b_\alpha, b_\gamma \in B$, neither containing the other, have a non-empty intersection that is not already an explicit hyponym, extend the basis B with the meaning postulate $b_\alpha \cap b_\gamma$. For example, "dog" is contained in both "carnivore" and "mammal." So, even though the core lexicon may not include an entry equivalent to "carnivorous mammal," it is a worthy meaning postulate, and the lexicon can be extended to include the intersection. Thus, B is a basis for S.

Because hyponymy is based on nested subsets, there is a hint of partial ordering on S. A partial order would be a big step towards establishing a metric.

At this point, a concrete example of a (very restricted) lexicon is in order. FIG. 3 shows a set of concepts, including "thing" 305, "man" 310, "girl" 312, "adult human" 315, "kinetic energy" 320, and "local action" 325. "Thing" 305 is the maximal element of the set, as every other concept is a type of "thing." Some concepts, such as "man" 310 and "girl" 312 are "leaf concepts," in the sense that no other concept in the set is a type of "man" or "girl." Other concepts, such as "adult human" 315, "kinetic energy" 320, and "local action" 325 are "internal concepts," in the sense that they are types of other concepts (e.g., "local action" 325 is a type of "kinetic energy" 320) but there are other concepts that are types of these concepts (e.g., "man" 310 is a type of "adult human" 315).

FIG. 4 shows a directed set constructed from the concepts of FIG. 3. For each concept in the directed set, there is at least one chain extending from maximal element "thing" 305 to the concept. These chains are composed of directed links, such as links 405, 410, and 415, between pairs of concepts. In the directed set of FIG. 4, every chain from maximal element "thing" must pass through either "energy" 420 or "category" 425. Further, there can be more than one chain extending from maximal element "thing" 305 to any concept. For example, there are four chains extending from "thing" 305 to "adult human"

315: two go along link 410 extending out of "being" 435, and two go along link 415 extending out of "adult" 445.

Some observations about the nature of FIG. 4:

- First, the model is a *topological space.*
- Second, note that *the model is not a tree.* In fact, it is an example of a *directed set.* For example, concepts "being" 430 and "adult human" 315 are types of multiple concepts higher in the hierarchy. "Being" 430 is a type of "matter" 435 and a type of "behavior" 440; "adult human" 315 is a type of "adult" 445 and a type of "human" 450.
- Third, observe that the relationships expressed by the links are indeed relations of hyponymy.
- Fourth, note particularly – but without any loss of generality – that "man" 310 maps to both "energy" 420 and "category" 425 (via composite mappings) which in turn both map to "thing" 305; i.e., the (composite) relations are multiple valued and induce a partial ordering. These multiple mappings are natural to the meaning of things and critical to semantic characterization.
- Finally, note that "thing" 305 is *maximal*; indeed, "thing" 305 is the *greatest* element of *any* quantization of the lexical semantic field (subject to the premises of the model).

Metrizing S

FIGs. 5A-5G show eight different chains in the directed set that form a basis for the directed set. FIG. 5A shows chain 505, which extends to concept "man" 310 through concept "energy" 420. FIG. 5B shows chain 510 extending to concept "iguana." FIG. 5C shows another chain 515 extending to concept "man" 310 via a different path. FIGs. 5D-5G show other chains.

FIG. 13 shows a data structure for storing the directed set of FIG. 3, the chains of FIG. 4, and the basis chains of FIGs. 5A-5G. In FIG. 13, concepts array 1305 is used to store the concepts in the directed set. Concepts array 1305 stores pairs of elements. One element identifies concepts by name; the other element stores numerical identifiers 1306. For example, concept name 1307 stores the concept "dust," which is paired with numerical

identifier "2" 1308. Concepts array 1305 shows 9 pairs of elements, but there is no theoretical limit to the number of concepts in concepts array 1305. In concepts array 1305, there should be no duplicated numerical identifiers 1306. In FIG. 13, concepts array 1305 is shown sorted by numerical identifier 1306, although this is not required. When concepts array 1305 is sorted by numerical identifier 1306, numerical identifier 1306 can be called the *index* of the concept name.

Maximal element (ME) 1310 stores the index to the maximal element in the directed set. In FIG. 13, the concept index to maximal element 1310 is "6," which corresponds to concept "thing," the maximal element of the directed set of FIG. 4.

Chains array 1315 is used to store the chains of the directed set. Chains array 1315 stores pairs of elements. One element identifies the concepts in a chain by index; the other element stores a numerical identifier. For example, chain 1317 stores a chain of concept indices "6", "5", "9", "7", and "2," and is indexed by chain index "1" (1318). (Concept index 0, which does not occur in concepts array 1305, can be used in chains array 1315 to indicate the end of the chain. Additionally, although chain 1317 includes five concepts, the number of concepts in each chain can vary.) Using the indices of concepts array 1305, this chain corresponds to concepts "thing," "energy," "potential energy," "matter," and "dust." Chains array 1315 shows one complete chain and part of a second chain, but there is no theoretical limit to the number of chains stored in chain array 1315. Observe that, because maximal element 1310 stores the concept index "6," every chain in chains array 1315 should begin with concept index "6." Ordering the concepts within a chain is ultimately helpful in measuring distances between the concepts. However concept order is not required. Further, there is no required order to the chains as they are stored in chains array 1315.

Basis chains array 1320 is used to store the chains of chains array 1315 that form a basis of the directed set. Basis chains array 1320 stores chain indices into chains array 1315. Basis chains array 1320 shows four chains in the basis (chains 1, 4, 8, and 5), but there is no theoretical limit to the number of chains in the basis for the directed set.

Euclidean distance matrix 1325A stores the distances between pairs of concepts in the directed set of FIG. 4. (How distance is measured between pairs of concepts in the directed set is discussed below. But in short, the concepts in the directed set are mapped to state vectors in multi-dimensional space, where a state vector is a directed line segment starting at

the origin of the multi-dimensional space and extending to a point in the multi-dimensional space.) The distance between the end points of pairs of state vectors representing concepts is measured. The smaller the distance is between the state vectors representing the concepts, the more closely related the concepts are. Euclidean distance matrix 1325A uses the indices 1306 of the concepts array for the row and column indices of the matrix. For a given pair of row and column indices into Euclidean distance matrix 1325A, the entry at the intersection of that row and column in Euclidean distance matrix 1325A shows the distance between the concepts with the row and column concept indices, respectively. So, for example, the distance between concepts "man" and "dust" can be found at the intersection of row 1 and column 2 of Euclidean distance matrix 1325A as approximately 1.96 units. The distance between concepts "man" and "iguana" is approximately 1.67, which suggests that "man" is closer to "iguana" than "man" is to "dust." Observe that Euclidean distance matrix 1325A is symmetrical: that is, for an entry in Euclidean distance matrix 1325A with given row and column indices, the row and column indices can be swapped, and Euclidean distance matrix 1325A will yield the same value. In words, this means that the distance between two concepts is not dependent on concept order: the distance from concept "man" to concept "dust" is the same as the distance from concept "dust" to concept "man."

Angle subtended matrix 1325B is an alternative way to store the distance between pairs of concepts. Instead of measuring the distance between the state vectors representing the concepts (see below), the angle between the state vectors representing the concepts is measured. This angle will vary between 0 and 90 degrees. The narrower the angle is between the state vectors representing the concepts, the more closely related the concepts are. As with Euclidean distance matrix 1325A, angle subtended matrix 1325B uses the indices 1306 of the concepts array for the row and column indices of the matrix. For a given pair of row and column indices into angle subtended matrix 1325B, the entry at the intersection of that row and column in angle subtended matrix 1325B shows the angle subtended the state vectors for the concepts with the row and column concept indices, respectively. For example, the angle between concepts "man" and "dust" is approximately 51 degrees, whereas the angle between concepts "man" and "iguana" is approximately 42 degrees. This suggests that "man" is closer to "iguana" than "man" is to "dust." As with Euclidean distance matrix 1325A, angle subtended matrix 1325B is symmetrical.

Not shown in FIG. 13 is a data structure component for storing state vectors (discussed below). As state vectors are used in calculating the distances between pairs of concepts, if the directed set is static (i.e., concepts are not being added or removed and basis chains remain unchanged), the state vectors are not required after distances are calculated. Retaining the state vectors is useful, however, when the directed set is dynamic. A person skilled in the art will recognize how to add state vectors to the data structure of FIG. 13.

Although the data structure for concepts array 1305, maximal element 1310 chains array 1315, and basis chains array 1320 in FIG. 13 are shown as arrays, a person skilled in the art will recognize that other data structures are possible. For example, concepts array could store the concepts in a linked list, maximal element 1310 could use a pointer to point to the maximal element in concepts array 1305, chains array 1315 could use pointers to point to the elements in concepts array, and basis chains array 1320 could use pointers to point to chains in chains array 1315. Also, a person skilled in the art will recognize that the data in Euclidean distance matrix 1325A and angle subtended matrix 1325B can be stored using other data structures. For example, a symmetric matrix can be represented using only one half the space of a full matrix if only the entries below the main diagonal are preserved and the row index is always larger than the column index. Further space can be saved by computing the values of Euclidean distance matrix 1325A and angle subtended matrix 1325B "on the fly" as distances and angles are needed.

Returning to FIGs. 5A-5G, how are distances and angles subtended measured? The chains shown in FIGs. 5A-5G suggest that the relation between any node of the model and the maximal element "thing" 305 can be expressed as any one of a set of *composite* functions; one function for each chain from the minimal node μ to "thing" 305 (the n^{th} predecessor of μ along the chain):

$$f: \mu \Rightarrow thing = f_1 \circ f_2 \circ f_3 \circ \cdots \circ f_n$$

where the chain connects $n + 1$ concepts, and f_j: links the $(n - j)^{th}$ predecessor of μ with the $(n + 1 - j)^{th}$ predecessor of μ, $1 \leq j \leq n$. For example, with reference to FIG. 5A, chain 505 connects nine concepts. For chain 505, f_1 is link 505A, f_2 is link 505B, and so on through f_8 being link 505H.

Consider the set of all such functions for all minimal nodes. Choose a countable subset $\{f_k\}$ of functions from the set. For each f_k construct a function g_k: $S \Rightarrow I^1$ as follows.

For $s \in S$, s is in relation (under hyponymy) to "thing" 305. Therefore, s is in relation to at least one predecessor of μ, the minimal element of the (unique) chain associated with f_k. Then there is a predecessor of smallest index (of μ), say the m^{th}, that is in relation to s. Define:

$$g_k(s) = (n - m) / n \qquad \text{Equation (2)}$$

This formula gives a measure of concreteness of a concept to a given chain associated with function f_k.

As an example of the definition of g_k, consider chain 505 of FIG. 5A, for which n is 8. Consider the concept "cat" 555. The smallest predecessor of "man" 310 that is in relation to "cat" 555 is "being" 430. Since "being" 430 is the fourth predecessor of "man" 310, m is 4, and g_k("cat" 555) = (8 - 4) / 8 = ½. "Iguana" 560 and "plant" 560 similarly have g_k values of ½. But the only predecessor of "man" 310 that is in relation to "adult" 445 is "thing" 305 (which is the eighth predecessor of "man" 310), so m is 8, and g_k("adult" 445) = 0.

Finally, define the vector valued function $\varphi: S \Rightarrow \mathbb{R}^k$ relative to the indexed set of scalar functions $\{g_1, g_2, g_3, \ldots, g_k\}$ (where scalar functions $\{g_1, g_2, g_3, \ldots, g_k\}$ are defined according to Equation (2)) as follows:

$$\varphi(s) = \langle g_1(s), g_2(s), g_3(s), \ldots, g_k(s) \rangle \qquad \text{Equation (3)}$$

This state vector $\varphi(s)$ maps a concept s in the directed set to a point in k-space ($\mathbb{R}^k$). One can measure distances between the points (the state vectors) in k-space. These distances provide measures of the closeness of concepts within the directed set. The means by which distance can be measured include distance functions, such as Equations (1a), (1b), or (1c). Further, trigonometry dictates that the distance between two vectors is related to the angle subtended between the two vectors, so means that measure the angle between the state vectors also approximates the distance between the state vectors. Finally, since only the direction (and not the magnitude) of the state vectors is important, the state vectors can be normalized to the unit sphere. If the state vectors are normalized, then the angle between two state vectors is no longer an approximation of the distance between the two state vectors, but rather is an exact measure.

The functions g_k are analogous to step functions, and in the limit (of refinements of the topology) the functions are continuous. Continuous functions preserve local topology; i.e., "close things" in S map to "close things" in $\mathbb{R}^k$, and "far things" in S tend to map to "far things" in $\mathbb{R}^k$.

Example Results

The following example results show state vectors $\varphi(s)$ using chain 505 as function g_1, chain 510 as function g_2, and so on through chain 540 as function g_8.

$\varphi(\text{"boy"}) \Rightarrow \langle 3/4, 5/7, 4/5, 3/4, 7/9, 5/6, 1, 6/7\rangle$

$\varphi(\text{"dust"}) \Rightarrow \langle 3/8, 3/7, 3/10, 1, 1/9, 0, 0, 0\rangle$

$\varphi(\text{"iguana"}) \Rightarrow \langle 1/2, 1, 1/2, 3/4, 5/9, 0, 0, 0\rangle$

$\varphi(\text{"woman"}) \Rightarrow \langle 7/8, 5/7, 9/10, 3/4, 8/9, 2/3, 5/7, 5/7\rangle$

$\varphi(\text{"man"}) \Rightarrow \langle 1, 5/7, 1, 3/4, 1, 1, 5/7, 5/7\rangle$

Using these state vectors, the distances between concepts and the angles subtended between the state vectors are as follows:

Pairs of Concepts	Distance (Euclidean)	Angle Subtended
"boy" and "dust"	~1.85	~52°
"boy" and "iguana"	~1.65	~46°
"boy" and "woman"	~0.41	~10°
"dust" and "iguana"	~0.80	~30°
"dust" and "woman"	~1.68	~48°
"iguana" and "woman"	~1.40	~39°
"man" and "woman"	~0.39	~07°

From these results, the following comparisons can be seen:

- "boy" is closer to "iguana" than to "dust."
- "boy" is closer to "iguana" than "woman" is to "dust."
- "boy" is much closer to "woman" than to "iguana" or "dust."
- "dust" is further from "iguana" than "boy" to "woman" or "man" to "woman."
- "woman" is closer to "iguana" than to "dust."

- "woman" is closer to "iguana" than "boy" is to "dust."
- "man" is closer to "woman" than "boy" is to "woman."

All other tests done to date yield similar results. The technique works consistently well.

How It (Really) Works

As described above, construction of the φ transform is (very nearly) an algorithm. In effect, this describes a *recipe* for metrizing a lexicon – or for that matter, metrizing anything that can be modeled as a directed set – but does not address the issue of *why* it works. In other words, *what's really going on here*? To answer this question, one must look to the underlying mathematical principles.

First of all, what is the nature of S? Earlier, it was suggested that a propositional model of the lexicon has found favor with many linguists. For example, the lexical element "automobile" might be modeled as:

{automobile: *is a* machine,
is a vehicle,
has engine,
has brakes,
...
}

In principle, there might be infinitely many such properties, though practically speaking one might restrict the cardinality to $\aleph_0$ (countably infinite) in order to ensure that the properties are addressable. If one were disposed to do so, one might require that there be only finitely many properties associated with a lexical element. However, there is no compelling reason to require finiteness.

At any rate, one can see that "automobile" is simply an element of the power set of **P**, the set of all propositions; i.e., it is an element of the set of all subsets of **P**. The power set is denoted as $\wp(\mathbf{P})$. Note that the first two properties of the "automobile" example express "*is a*" relationships. By "*is a*" is meant entailment. *Entailment* means that, were one to intersect the properties of every element of $\wp(\mathbf{P})$ that is called, for example, "machine," then the

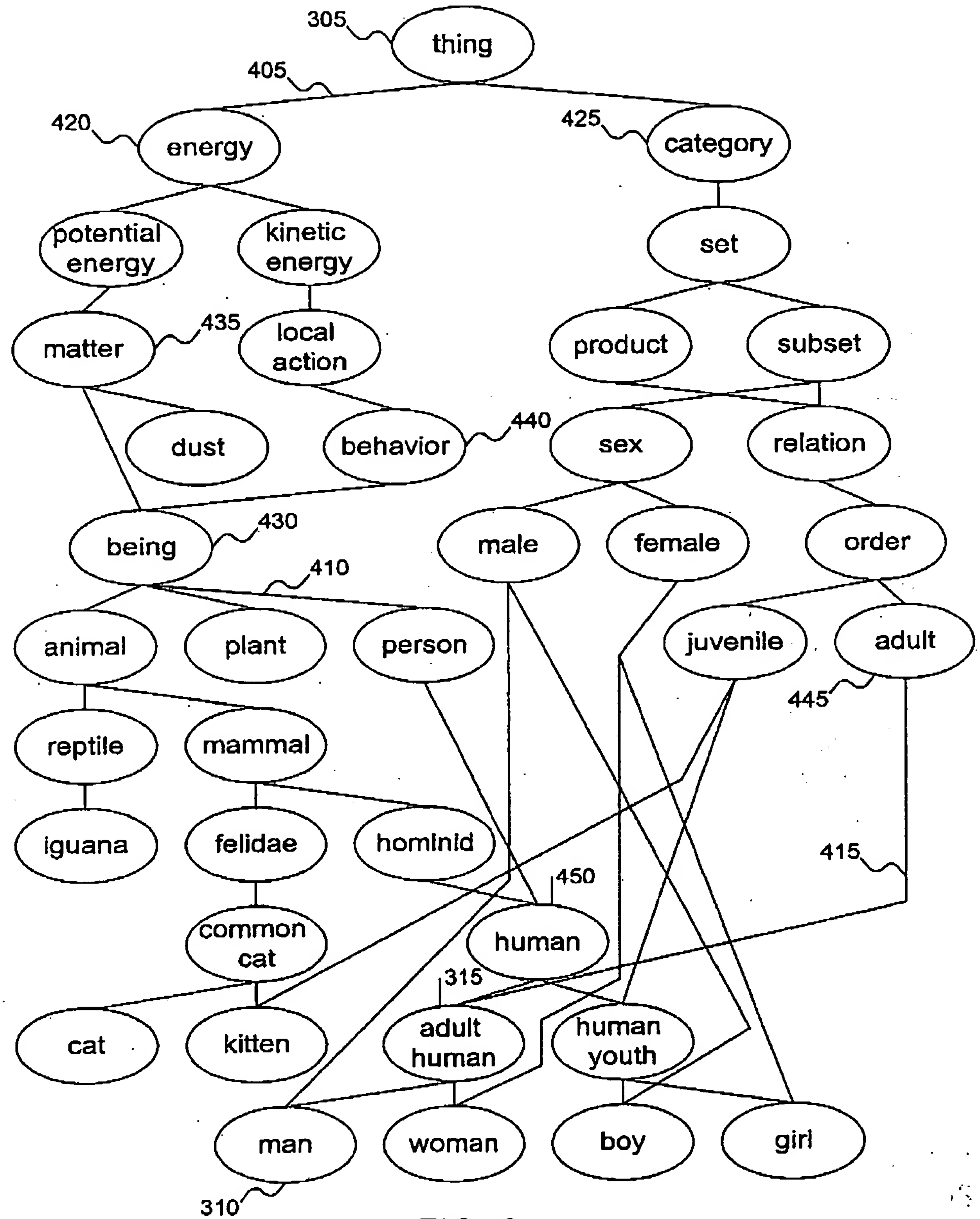

305
thing
405
420
energy
425
category
potential energy
kinetic energy
set
matter
435
local action
product
subset
dust
behavior
440
sex
relation
being
430
male
female
order
410
animal
plant
person
juvenile
adult
445
reptile
mammal
iguana
felidae
hominid
415
450
human
common cat
315
cat
kitten
adult human
human youth
man
woman
boy
girl
310

FIG. 4

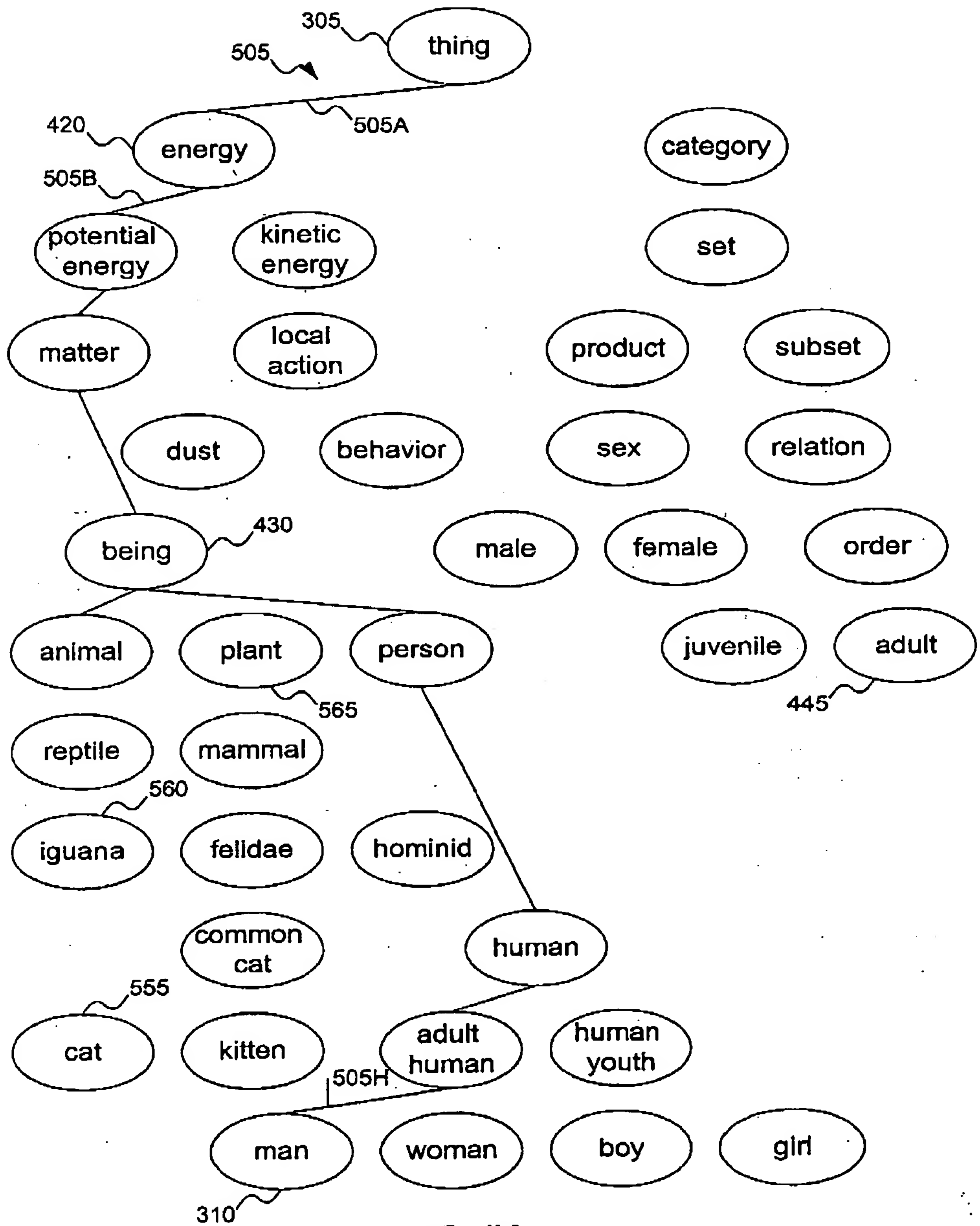

305
thing
505
505A
420
energy
category
505B
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
430
male
female
order
animal
plant
person
juvenile
adult
565
445
reptile
mammal
560
iguana
felidae
hominid
common cat
human
555
cat
kitten
adult human
human youth
505H
man
woman
boy
girl
310

FIG. 5A

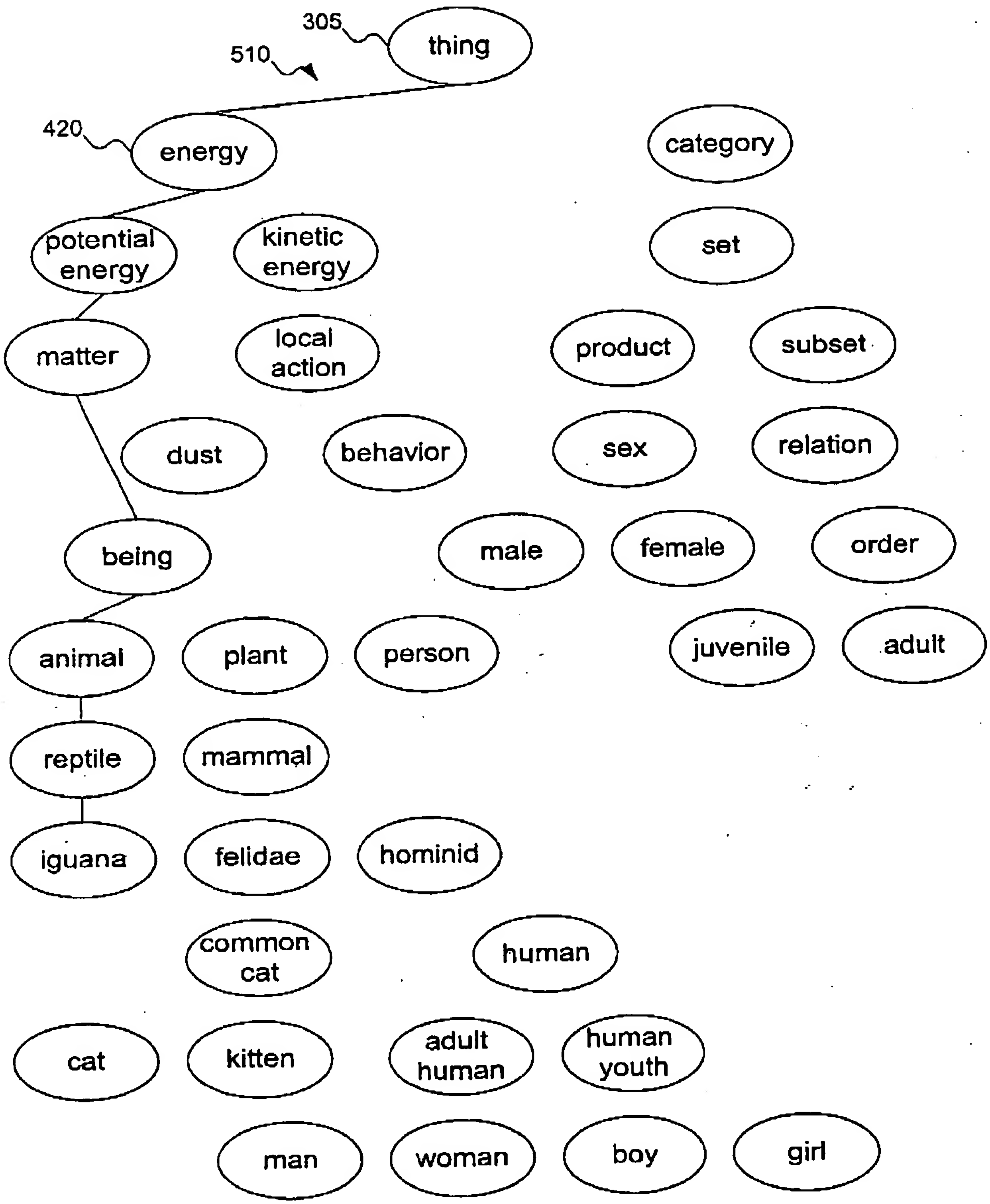
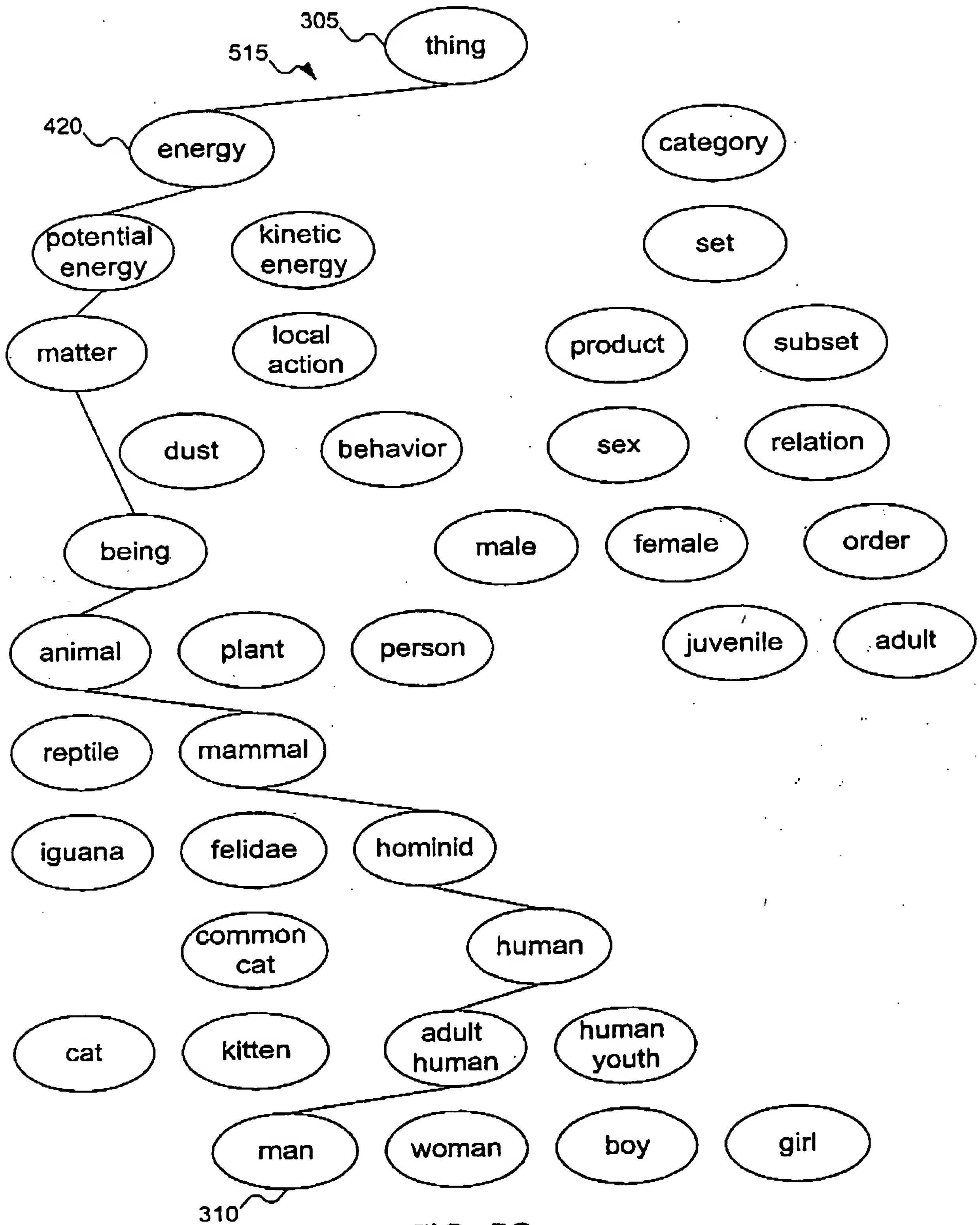

305
thing
510
420
energy
category
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
male
female
order
animal
plant
person
juvenile
adult
reptile
mammal
iguana
felidae
hominid
common cat
human
cat
kitten
adult human
human youth
man
woman
boy
girl

FIG. 5B



305
515
thing
420
energy
category
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
male
female
order
animal
plant
person
juvenile
adult
reptile
mammal
iguana
felidae
hominid
common cat
human
cat
kitten
adult human
human youth
man
woman
boy
girl
310

FIG. 5C

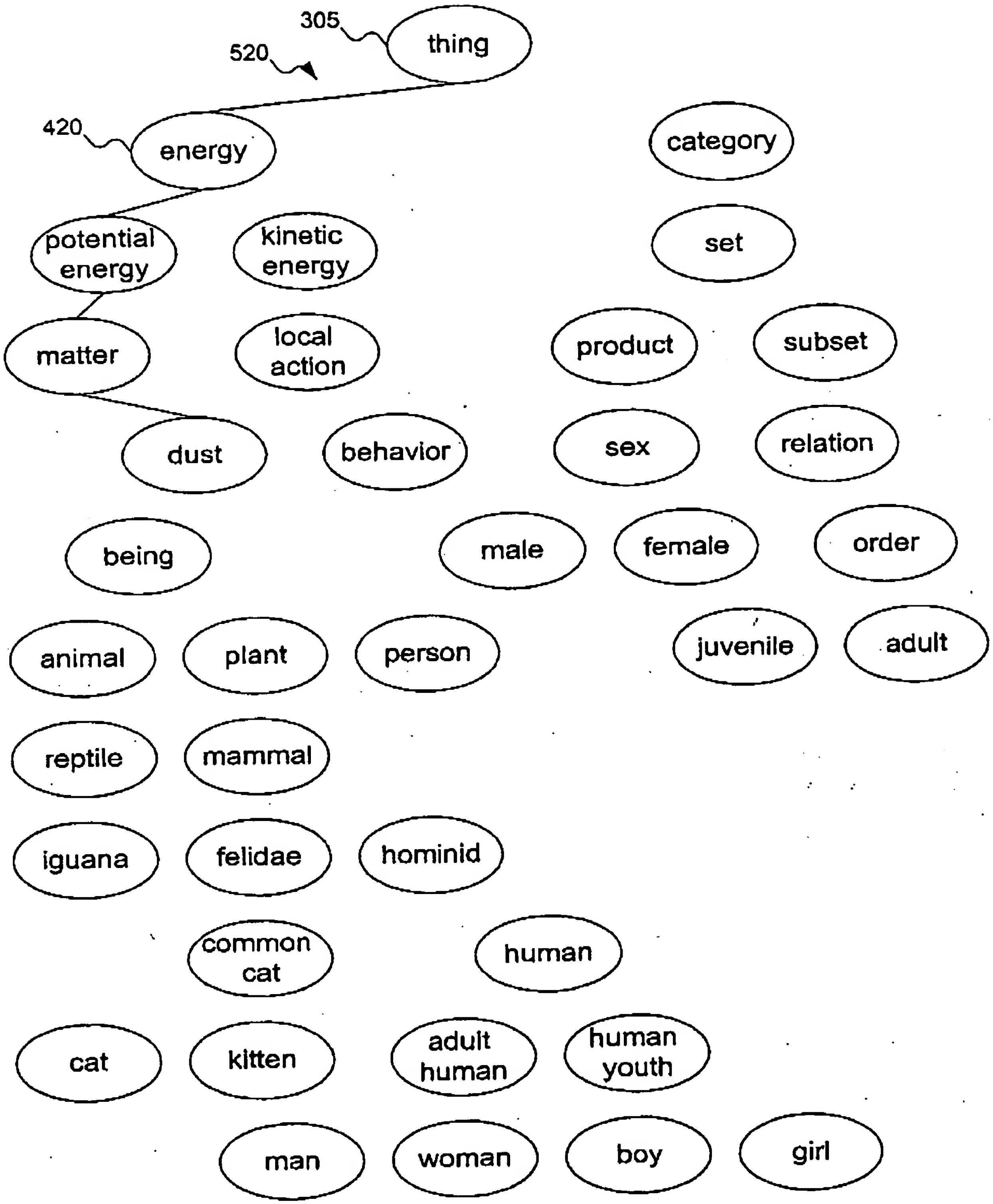
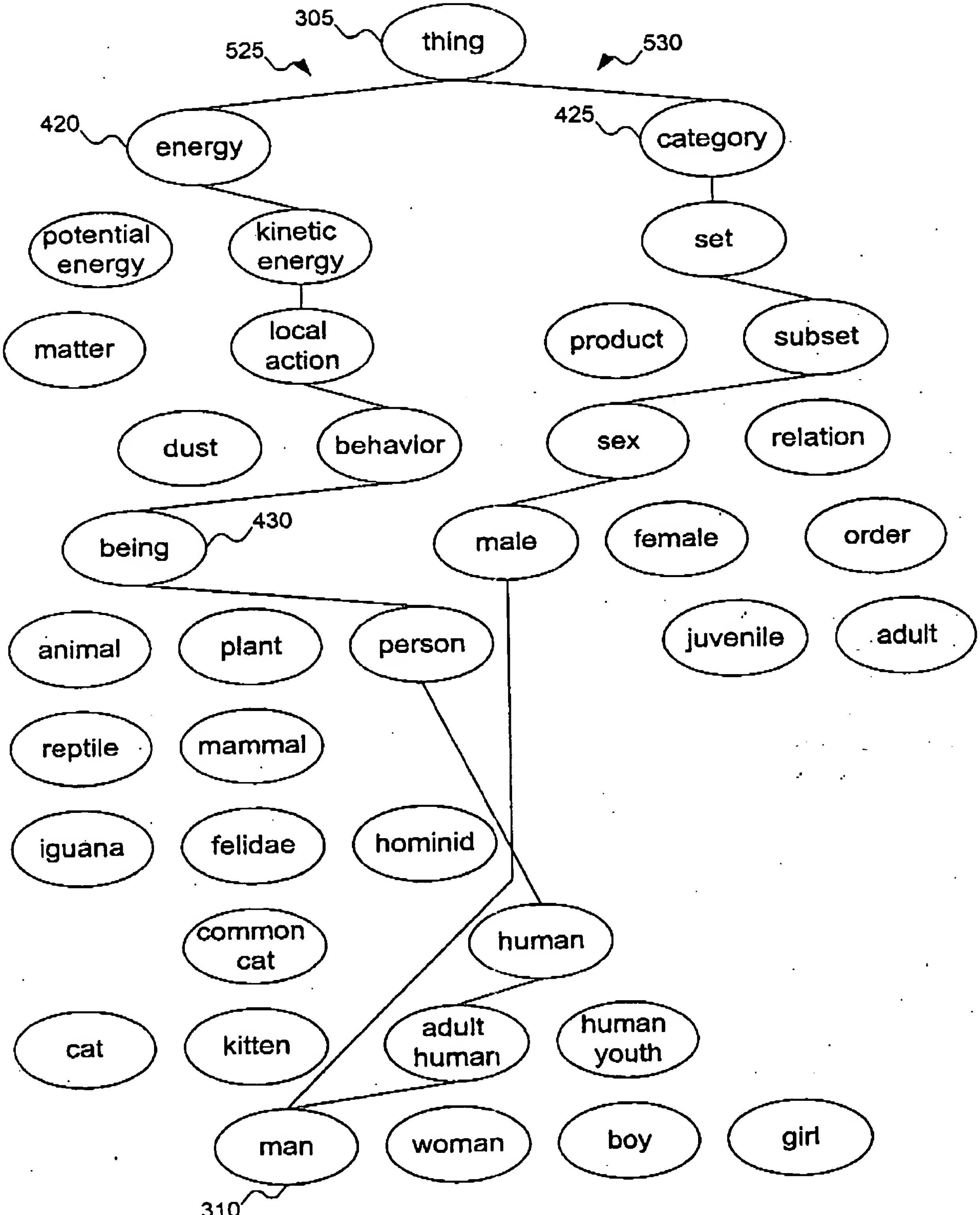

305
520
thing
420
energy
category
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
male
female
order
animal
plant
person
juvenile
adult
reptile
mammal
iguana
felidae
hominid
common cat
human
cat
kitten
adult human
human youth
man
woman
boy
girl

FIG. 5D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thing
525
530
420
energy
425
category
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
430
male
female
order
juvenile
adult
animal
plant
person
reptile
mammal
iguana
felidae
hominid
common cat
human
cat
kitten
adult human
human youth
man
woman
boy
girl
310

FIG. 5E

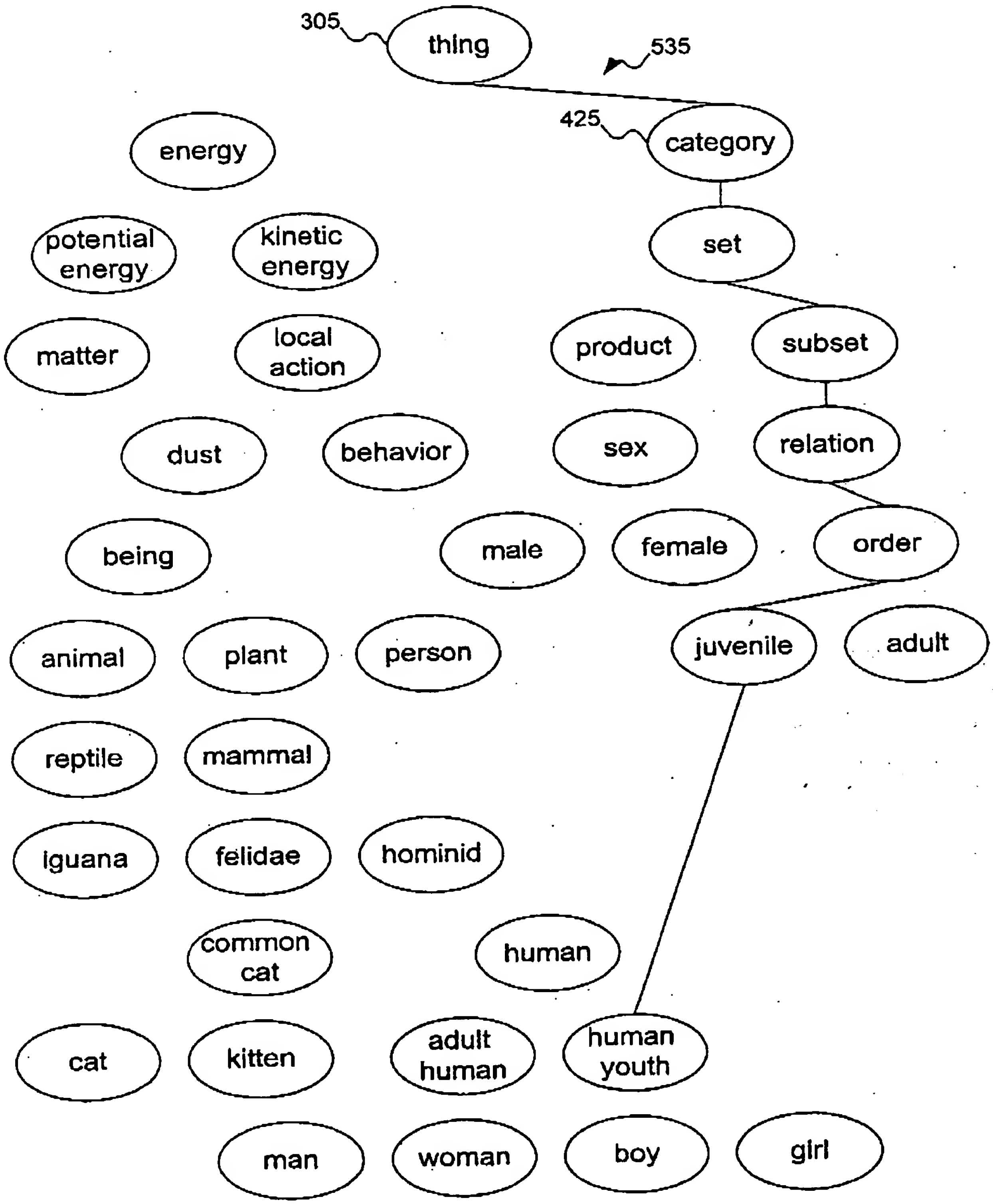
305
thing
535
425
category
energy
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
male
female
order
animal
plant
person
juvenile
adult
reptile
mammal
iguana
felidae
hominid
common cat
human
cat
kitten
adult human
human youth
man
woman
boy
girl

FIG. 5F

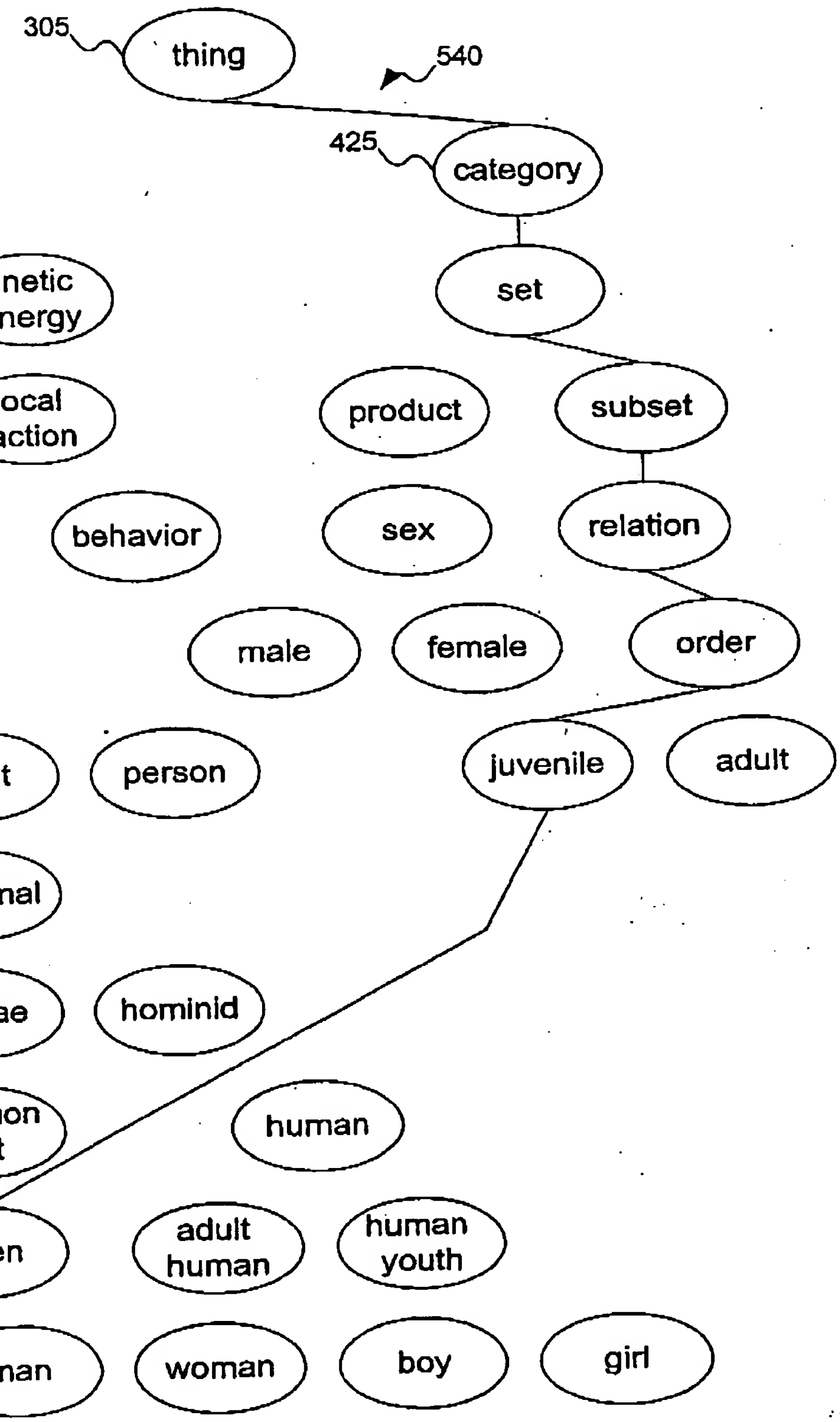
305
thing
540
425
category
energy
potential energy
kinetic energy
set
matter
local action
product
subset
dust
behavior
sex
relation
being
male
female
order
animal
plant
person
juvenile
adult
reptile
mammal
iguana
felidae
hominid
common cat
human
cat
kitten
adult human
human youth
man
woman
boy
girl

FIG. 5G